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FINAL RESEARCH REPORT

VALIDATION OF
MULTIATTRIBUTE UTILITY PROCEDURES

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December, 1982

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This report summarized the research conducted under DARPA Contract No. MDA093-81-C-0203. For this contract we examined validation topics through both a real-world and laboratory setting. In the laboratory experiments we taught subjects additive and multiplicative value functions via outcome feedback. We found that standard MAUM procedures recovered the taught functions. We also found behavioral differences between value and utility elicitation

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gauge the validity of alternative multiattribute utility elicitation techniques. The results indicate that subjects learned the value functions very well, independently of whether the problem involved two or four attributes, equal or unequal weights, additive or multiplicative functions. Riskless value and risky utility elicitation methods were able to identify the structural properties of the taught models (additive vs. multiplicative, sign of the interaction parameter) quite well, although risky methods generated a tendency towards multiattribute risk aversion in additive models. Furthermore, for the simple models (e.g. additive, equal weight, and multiplicative equal weight), the standard elicitation methods were able to recapture the taught model parameters quite well. The ability of multiattribute utility techniques to recover value functions decreased, however, when models became very complex (e.g. multiplicative unequal weights). In these cases simple methods like ratio weighting and a hybrid combination of methods outperformed the "formally correct" methods.

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VALIDATION OF MULTIATTRIBUTE UTILITY PROCEDURES

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VALIDATION OF MULTIATTRIBUTE UTILITY PROCEDURES

Introduction

The experiments of this period were concerned with validation of decision analytic tools in both a real-world and a laboratory setting. Our previous work has suggested that in many instances decision analytic procedures can improve human performance, and that simplification of the technology will extend its potential uses. Thus a major thrust in past research has been on simplification with concomitant validation of the simplified tools. The work of this contract period has expressly tested the limits of our previous work and suggests areas where more validation and/or exploration is needed and potential situations where simplification should be approached rather more cautiously than was previously thought.

Two studies were performed. The first consisted of two laboratory experiments, which used an extension of the Multiple Cue Learning Paradigm (MCPL) developed in this laboratory to pit several different decision analytic techniques against each other across conditions with different underlying "true" structural models. The other study applied Edwards's Simple MultiAttribute Rating Technique (SMART) (Edwards, 1977; Edwards and Newman, 1982)), to a complex real world evaluation problem. This report will summarize the findings and lessons of the work. For more detailed descriptions see Griffin and Edwards (1982) and John and von Winterfeldt (1982).

Teaching and Recovering Additive and Multiplicative Value Functions

As a technology matures one expects the precision of its application to be refined, subtleties to be explored, and in general,

the implications of theory and the practicalities of application to be more fully integrated. In Multiattribute Utility measurement (MAUM) such refinements include an exploration of the measurement theoretic bases of the model (e.g. risky vs. riskless models or, "utility" vs. "value"); the structural form of the multiattribute model (e.g. additive vs. multiplicative); and the functional forms of the single-attribute value or utility functions (e.g. linear vs. non-linear).

The two experiments of the laboratory study (reported by John and von Winterfeldt, 1982) compared several assessment techniques, which varied on the above dimensions across a range of "true" riskless multiattribute structures. We were primarily interested in the validity with which simple methods and models could recover complex "true" value structures. The unexpected results of these experiments answer questions about the validity of structures that had previously not been addressed.

Three different assessment techniques were used in this study. Two of them arise out of formal measurement-theoretic models for quantifying preference. One of the methods is formally appropriate for eliciting value functions and structures; that is, models of preference modeled without risk. The other, a utility method, is formally appropriate for modeling risky choice. Our final assessment technique is of the kind proposed by Edwards (1977) and others, which is not based upon strict measurement theory, but upon the psychology of numerical estimates of subjective quantities: magnitude scaling. This technique follows the logic of value or utility theory but includes judgments that have no strict measurement theoretic justification, and uses additive models without formal independence

checks.

Edwards and his colleagues (see Edwards, 1977; Edwards and Newman, 1982) have argued that:

1. Additive aggregation rules are good approximations to nonadditive (e.g., multiplicative) rules;

2. Linear single-attribute value functions are good approximations to non-linear (e.g., exponential) forms;

3. Questions about strengths of preference and/or gambles are difficult for respondents to understand; whereas ratings on attributes (location measures) and judgments of relative importance (weights) are more intuitive;

4. The lack of an error theory in both value and utility .rement raises the possibility that more complex models of preference are more susceptible to "random" errors that could lead to greater overall error tham found with (structurally incorrect) atheoretical rating scale models.

Previous work (both theoretical and empirical) in this research program has demonstrated that these assertions are often valid.

The unique feature of this study was to compare these three techniques across a variety of additive and nonadditive models. To do this subjects were "taught" value models through outcome feedback. Across conditions the number of attributes was varied as was the structural form of the model (i.e. additive vs. multiplicative), and the "strength" (in the multiplicative conditions) of the interaction term.

Experiment I

Twenty undergraduates were taught one of five different two-attribute models of diamond worth. Each subject saw 100 "diamond profiles" on a video display, estimated the value of each diamond, and received outcome feedback about the "actual" value of the diamond.

Models taught varied the trade-off between "quality" and "size." Trade-offs were either additive or multiplicative, and multiplicative models were either complementing or substituting. For the additive models the weight ratios (trade-offs) were either 4:1 or 1:1. Complementing models used either 2:1 or 1:1 weights and the substituting models used 1:1 weights. All five models used single-attribute value functions linear in "quality" and "size," the two variables comprising each diamond profile.

Following training, each subject met with one of two analysts who knew nothing about what model the subject had been taught. Analysts guided subjects through a series of questions about critical value-differences, direct subjective estimates of "importance weight" ratios, and gamble indifferences of two kinds, basic reference lottery tickets (BRLTS) and certainty equivalents.

Models of each subject's judgments were constructed based on the analyst's session and the last 50 estimates the subjects gave during the computer session. Four multiattribute models were constructed from the analyst-session judgments. A multiplicative value model assuming linear single-attribute value functions was constructed from value difference judgments. Two "importance weight" models (one additive and one multiplicative) were constructed from the importance weight judgment and (in the multiplicative case) one value judgment.

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And finally, a utility model, assuming linear single-attribute utility functions, was constructed from lottery judgments. The bootstrapped models based on the last 50 trials of the computer session included both an additive and multiplicative functional form model.

This experiment demonstrated that subjects could learn both additive and nonadditive trade-off relations, and that these newly acquired value structures could be successfully discovered via standard multiattribute value and utility assessment procedures.

However, these general positive findings on the validity of the paradigm and the assessment techniques have to be tempered with specifics. For instance, we found the value and utility models to be an improvement over the additive importance-weight models when the taught model was multiplicative. In contrast, when the model taught was additive the elicited value and utility models did not tend to capture that additivity (i.e. the interaction term was non-zero). Teaching unequal weights models decreased the performance of the elicited models, particularly so for the utility models.

All of these findings apply to the somewhat restricted two-attribute case. The second experiment attempted to replicate our findings using four attributes.

Experiment II

Ten undergraduates were taught one of five different four-attribute models of diamond worth. The training procedure was similar to that in Experiment I, except that diamonds were described in terms of the four Cs; cut, color, clarity, and carast. Just as in Experiment I, true models were either additive, complementing, or substituting. Weights for additive and complementing models were

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either all equal, or in the ratio 4:3:2:1. Only an equal weights substituting model was used. Following computer training sessions subjects went through an analyst session where the same types of judgments as in Experiment I were elicited.

The results of the computer sessions replicated the finding of Experiment I that subjects could learn both additive and non-additive trade-off relations in the more general four-attribute case. From the elicitation sessions we found that complementing and substituting models were recoverable (that is the elicited interaction term was non-zero and appropriately signed). However, utility-based models showed a marked shift towards substitution, for which one interpretation is risk aversion.

Weights were not well recovered by any of the techniques. In general, though, value models produced the steepest weights and utility procedures produced the flattest weights. As in the two attribute experiment, non-linear single attribute functions were not recovered.

Summary and conclusions

The most important and clearest findings of the study were that multiplicative (as well as additive) trade-off structures can be learned through outcome feedback and reliably recovered using standard value and utility assessment techniques. We found this in both the two- and four-attribute experiments. The multiplicative models were typically "better" than the additive importance-weight models when a multiplicative model was taught.

From the experiments we conclude that:

1) Subjects can learn additive and multiplicative value models via

outcome feedback and that functional form of the taught model is recoverable through standard value and utility assessment techniques;

2) Distinctions among value, utility, and importance weight elicitation techniques are behaviorally observable.

Two explanations of the consistent differences between the value and utility model compete. Such differences can be primarily consequences of a consistent response mode bias, or of a psychologically valid distinction between the two techniques. We believe that response mode bias causes the steepened weights. But we do not know why utility models produce more substituting (or risk averse) models. More research, perhaps with taught utility models, is indicated.

Although subjects were clearly able to learn and reproduce multiplicative models using the standard assessment procedures, the practical implications of this finding are not clear. An assessed multiplicative model will perform better than an additive one when the true model is multiplicative, but how much better is equivocal. "Better" can be defined by several different measures of agreement. More important, the significance of the improvement is highly dependent upon the decision problem at hand.

The three primary variables controlling model agreement that may vary from one problem context to another are:

1. The multivariate distribution of alternatives along attributes;
2. The choice problem, e.g., choose the one best alternative, choose the best X%, rank order all, etc., and
3. The standard against which differences in actual obtained value

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(utility) is to be compared.

Furthermore, different measures of agreement make different implicit assumptions about these variables. And again, an increment in model agreement (as measured by a correlation coefficient) is still dependent upon the context. A .04 increment may translate into pennies or thousands of dollars depending on the particular context.

"SMART" Models

Our second study attempted to replicate and extend the findings of Stillwell's (1980) work with bank loan officers and MAUM methods. Stillwell used credit card applications as stimuli. Outcome information was available; a large-scale empirically based discriminant analysis model classified the applications as either "good" or "bad." Stillwell's study compared several different MAUM elicitation techniques and one holistically based decomposition technique. He concluded that all of the decomposed techniques worked very well except for the holistic one. He concluded that ease of application should be a major determinant of the selection among decomposition techniques.

A criticism of the study was that all of the subjects were familiar with the empirical discriminant model before the experiment. Therefore, the officers might have simply been reproducing the parameters of a model they already knew.

A better real-world study would incorporate outcome information with substantive expertise that did not include specific knowledge about a decomposed model. The current study attempted to do this.

Subjects and Task

Subjects in the experiment were 20 Loan Examiners working for a major California bank in its Credit Review Department. Credit review functions to evaluate the quality of credit that the bank has already granted. It is independent of the sales department and is organizationally a part of the office of the controller of the bank.

The task was to construct SMART models of a loan examination. In the course of their jobs, loan examiners evaluate already-granted credit and rate it based on a large amount of information about such things as financial statements, quality of management, type of industry, economic conditions, etc. The loans are either "criticized" or "passed." Criticized loans are considered to be serious financial exposures for the bank, and the bank's cash reserves in part depend upon these judgments. We had access to a data bank that contained pass/criticize outcome information based on the entire set of data typically used for the judgments, and end-of-year financial statements for about 100 firms. The firms were all mid-sized wholesalers, retailers, or manufacturers. The data base was about evenly split between passed and criticized loans, although in the population criticized loans for firms of this size are fairly rare.

Subjects were run individually by experimenters who had decision-analytic training. Subjects were given the population domain of their judgments. All of the subjects' judgments were based only upon the end-of-year financial statements. Subjects provided 20 holistic evaluations of ten passed and criticized loans randomly selected from the data base. Subjects judged whether they thought the firm should be criticized or passed and gave an anchored numerical

judgment (with 0 representing certain criticism, 500 complete uncertainty, and 1000 certain pass.)

Next the subjects completed two SMART value models which also used only financial statement variables. In one of the models the attributes were preselected using statistical techniques. In the other, subjects selected financial variables for the models. Order of the SMART models was counterbalanced.

Time constraints did not allow for the elicitation of single dimension value functions. As a proxy, we used z-score transformations to give all attributes the same mean and standard deviation.

Results

The basic design of the experiment was a simple three-condition within-subjects design. The primary dependent variable was the percentage of correct classification. For the SMART models, we individually applied each model to the bank's database. The holistic judgments were made on cases taken from the database.

Results indicated that all models correctly classified approximately the same number of correct cases (around 70%). This is fairly comparable to the rate of classification that is produced by a least-square discriminant model. A maximum likelihood logistic discriminant model, however, produces somewhat better estimates (about 75% correct classification).

The accuracy of the SMART models did not appear to be dependent upon the number of attributes subjects selected for their models. The number of attributes in the self selected models ranged from three to nine, with a mean of about six. The SMART models with pre-selected

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attributes had five attributes.

Some background information was collected on each of the subjects. This data indicated a marginal tendency for experience and age to produce both holistic and SMART judgments that were less accurate. (Experience was measured with two (related) variables: number of years working at the particular bank; and number of years working for any financial institution.)

Conclusions.

The ad hoc nature of the SMART modeling should serve to qualify the results. Essentially, the SMART models had everything going against them, and yet performed at the same level as the holistic and close to the level of the more elaborate statistical models. Making holistic judgments based on financial statements is a task that all of the loan examiners have substantial expertise in. No subjects, so far as we were able to tell, had any experience with MAUM.

Furthermore the time constraints prevented elaborate structuring, or the elicitation of more precise single dimension value functions. Had we structured more fully, taking into account, for instance, the specific nature of the businesses, we almost certainly would have increased the accuracy of classification. From an application perspective, this has a possible application. Since these very simple decomposed judgment based models did just about as well as the statistical models based on the large data-base, such models might be useful as a "red flag" system in other situations where a data base is not readily available. (The current bank data-base required searching seven years of records.)

For validation purposes the results are encouraging but not

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conclusive. Taken with the results of Stillwell's study they point to further work. In Stillwell's study the structure and selection of attributes was predetermined. The bank spent both large amounts of time and money determining the attributes, in addition to the computational work involved in the discriminant analysis. The current study had to rely on fairly "quick and dirty" structuring. SMART provided a high level of accuracy in Stillwell's study, and a moderate level in the current one. Since a least-squares discriminant model also provides a lower level of accuracy, it is probably the case that the structuring is at fault. Further work on structuring is needed for this particular type of application. Further work is needed in general on structuring for scientific purposes.

We feel the finding that experience and age tended to marginally produce less accuracy in the holistic and decomposed judgments to be more a function of recalcitrance on the part of the older subjects rather than a true cognitive deficit in the ability to implement MAUM or make the holistic judgments. Older subjects tended to express reluctance in making any of the judgments based simply on the one year of financial statements.

IV. Conclusions

Our studies on validating multiattribute utility techniques have taken a two-pronged approach: real world validation in settings that have an outcome criterion, and laboratory validation with teaching and recovering value functions using standard MAUM assessment techniques. The two experiments reported in this final report reflected this validation strategy, and their results fit into an emerging story of the validity of MAUM.

The first part of the story is about simplicity. Our results indicate that simple approximate models and assessment techniques do as well or better than complex ones if, in fact, the "true" model is simple. This was a result of Stillwell (1981) as well as of John et al. (1982) and it is replicated in the present MCPL experiment. If the true models become more complex, the more complicated elicitation techniques show some improvement over the simple approximation techniques. This result was especially obvious in analyzing taught multiplicative value functions in the MCPL study. Surprisingly, however, if the true model is very complex, simple assessment techniques appear to do relatively well again.

The second part of the emerging validation story is about error. No multiattribute utility model or technique is perfect. In the MCPL studies, we were struck by the lack of ability of the MAU techniques to recover the weights in complex four-attribute value functions. Furthermore, while the model form could usually be identified, the elicited interaction parameters were frequently quite far off the true ones. Finally, in the bank study, the SMART model did not show exceptional performance in classifying criticisms of bank loans correctly. The fault in both studies may not lie so much with the models as with the complexity of the underlying structures. In the MCPL study accuracy degraded with the complexity of the model structure (multiplicative, unequal weights); in the bank study the complexity was introduced by the real world problem itself -- the structure imposed was probably much too simple to capture that complexity. Complexities in real world structures and in the models applied to them seem to harm MAUM techniques.

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The lessons of our validation studies suggest two strategies for coping with complex structures and models. The first would attempt to reduce the complexity in the problem structures, essentially by a continued search for simple and independent sets of attributes that lend themselves to more additive modeling. The second strategy is to increase model complexity -- up to a point. If there are reasons to believe that the underlying preferences are non-additive, and if the deviations from additivity are not gross or extreme, and if restructuring does not help, then one should probably attempt somewhat more complex models and assessment techniques. But our results suggest reversion to simple approximations if the structures of underlying preference forms become overly complex. In those cases the more complex elicitation forms are unlikely to detect correctly the subtleties of the complex realities, and, worst yet, may lead the analysis further astray.

References

Edwards, W. Research on the technology of inference and decision
(Tech. Rep. 011313-F). Ann Arbor, Mich.: University of
Michigan, Engineering Psychology Laboratory, November, 1973.

Edwards, W., Research on the technology of inference and decision
(SSRI Tech. Rep. 75-10). Los Angeles: University of Southern
California, Social Science Research Institute, August 1975.

Edwards, W. "How to use multiattribute utility measurement for social
decision making." IEEE Transactions on Systems, Man and
Cybernetics, 1977, 7, 326-340.

Edwards, W., John, R.S. & Stillwell, W., Research on the technology of
inference and decision (SSRI Tech. Rep. 77-6). Los Angeles:
University of Southern California, Social Science Research
Institute, November, 1977.

Edwards, W., John, R.S., & Stillwell, W. Research on the technology
of inference and decision (SSRI Tech. Rep. 79-1). Los Angeles:
University of Southern California, Social Science Research
Institute, January, 1979.

Edwards, W., John, R.S., & von Winterfeldt, D. Structuring and
judgment in decision technology. Los Angeles: University of
Southern California, SSRI Final Report, 81-4.

Edwards, W. & Newman, J.R. Multiattribute Evaluation. Beverly Hills:
Sage Publications, Inc., 1982.

Edwards, W. & Seaver, D.A., Research on the technology of inference
and decision (SSRI Tech. Rep. 76-7). Los Angeles: University of
Southern California, Social Science Research Institute, October,
1976.

Edwards, W. & Stillwell, W., Validation, error, and simplification of decision technology (SSRI Tech. Rep. 80-5). Los Angeles: University of Southern California, Social Science Research Institute, June, 1980.

Griffin, G. & Edwards, W. SMART Models of Commercial Loan Classification. Los Angeles: University of Southern California, SSRI Technical Report 82-3, 1982.

John, R. & von Winterfeldt, D. Learning and Recovering Additive and Multiplicative Value Functions: A Criterion Validation of Multiattribute Utility Techniques. Los Angeles: University of Southern California, SSRI Technical Report 82-2, 1982.

Stillwell, W. Evaluating credit applications: A validation of multiattribute utility weight elicitation techniques and the additive model against a real world criterion. Organizational Behavior and Human Performance, 1980, in press.

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o To disseminate information to relevant public and social agencies in order to provide decision makers with the tools and ideas necessary to the formulation of public social policy.

HISTORY:

The Social Science Research Institute, University of Southern California, was established in 1972, with a staff of six. Its current staff of researchers and support personnel numbers over 50. SSRI draws upon most University academic Departments and Schools to make up its research staff, e.g. Industrial and Systems Engineering, Medicine, Psychology, Safety and Systems Management, and others. Senior researchers have joint appointments and most actively combine research with teaching.

RESEARCH INTERESTS:

Each senior SSRI scientist is encouraged to pursue his or her own research interests, subject to availability of funding. These interests are diverse. Four major interests persist among groups of SSRI researchers: crime control and criminal justice, use of administrative records for demographic and other research purposes, exploitation of applications of decision analysis to public decision making and program evaluation, and evaluation of radiological procedures in medicine. But many SSRI projects do not fall into these categories. Most projects combine the skills of several scientists, often from different disciplines. As SSRI research personnel change, its interests will change also.